

Teaching and learning inspired optimization algorithms: A review

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Abstract: Social Human Behaviour algorithms are the next step in nature inspired algorithms development. In the past decade these are proved to be useful for various optimisation tasks. The paper provided a global preview of existing algorithms of this kind and focused on two specific algorithms, inspired by teaching and learning process: Teaching-Learning Based Optimization and Group Teaching Optimisation algorithms. The algorithms' structure and flow are thoroughly explained and illustrated. A preview of algorithms' application is reported, based on the recent research. It is concluded that this kind of algorithms can be applied in various industry areas and that further research in this field is required.

Keywords: *TLBO; GTO; algorithm; teaching; learning*

1. INTRODUCTION

Some of nature-inspired algorithms that have been developed in the last 30 years are inspired by social human behavior and their interaction. Humans, as the most intelligent beings, perform various activities in different ways and find a problem solution. This has inspired various scientists to use it to develop different algorithms to optimize the various tasks that people solve. Some algorithms are based on the inspiration of learning and teaching that is performed in educational systems. There are different variations of algorithms and their implementations are also diverse. Applications of these algorithms are in manufacturing systems, control systems, energy systems, robotics, logistic, etc [1]. Algorithms are applied in order to optimize certain processes and there are a large number of scientific papers that show their application. Hybrid algorithms are also used, which combine several algorithms and thus improve various processes [1].

2. THEORETICAL BACKGROUND

There are a number of algorithms that are based on social human behavior. These algorithms are inspired by human interaction, walking, running, speaking, thinking, politics, teaching, learning,...

Every human has their own way of performing specific activities that affect their output. This has motivated many researchers to develop these types of algorithms [2]. Popular human based algorithms are presented in Table 1.

In this paper, we will explain two similar algorithms based on teaching and learning, Teaching-Learning Based Optimization (TLBO) algorithm and Group Teaching Optimization (GTO) algorithm. Popular human-based algorithms are presented in Table 1.

Table 1. *Social Human Behavior algorithms*

Algorithm Name	Acronym	Year
Adolescent Identity Search Algorithm	AISA	2020
Anarchic society Optimization	ASO	2012
Brain Storm Optimization Algorithm	BSO.2	2011
Bus Transportation Algorithm	BTA	2019
Collective Decision Optimization Algorithm	CDOA	2017
Cognitive Behaviour Optimization Algorithm	COA.3	2016
Competitive Optimization Algorithm	COOA	2016
Community of Scientist Optimization Algorithm	CSOA	2012
Cultural Algorithms	CA	1999
Duelist Optimization Algorithm	DOA	2016
Football Game Inspired Algorithms	FCA.1	2009
FIFA World Cup Competitions	FIFAAO	2016
Golden Ball Algorithm	GBA	2014
Global/Best Brain Storm OA	GBSO	2017
Group Counseling Optimization	GCO	2010
Group Leaders Optimization Algorithm	GLOA	2011
Greedy Politics Optimization Algorithm	GPO	2014
Group Teaching Optimization Algorithm	GTOA	2020
Human Evolutionary Model	HEM	2007
Human Group Formation	HGF	2010
Human/Inspired Algorithms	HIA	2009
Ideology Algorithm	IA	2016
Imperialist Competitive Algorithm	ICA	2007
Kho-Kho Optimization Algorithm	KKOA	2020
League Championship Algorithm	LCA.1	2014
Leaders and Followers Algorithm	LFA	2015
Old Bachelor Acceptance	OBA	1995
Oriented Search Algorithm	OSA	2008
Parliamentary Optimization Algorithm	POA	2008
Queuing Search Algorithm	QSA.1	2018
Social Behaviour Optimization Algorithm	SBO.1	2003
Social Cognitive Optimization	SCO	2002
Social Cognitive Optimization Algorithm	SCOA	2010
Social Emotional Optimization Algorithm	SEOA	2010
Stochastic Focusing Search	SFS	2008
Soccer Game Optimization	SGO	2012
Soccer League Competition	SLC	2014
Team Game Algorithm	TGA	2018
Teaching-Learning Based Optimization	TLBO	2011
Tug of War Optimization	TWO	2016
Unconscious Search	US	2012
Volleyball Premier League Algorithm	VPL	2017
Wisdom of Artificial Crowds	WAC	2011

3. TLBO ALGORITHM

The TLBO algorithm is based on the results of teacher's influence on student knowledge. Teachers

are expected to have the best knowledge of the subject they teach and to educate students with their hard work. When this interaction between teachers and students is over, students enter into communication with other students to further improve the acquired knowledge [3].

The algorithm consists of two phases (Fig. 1):

- teacher phase and
- student phase.

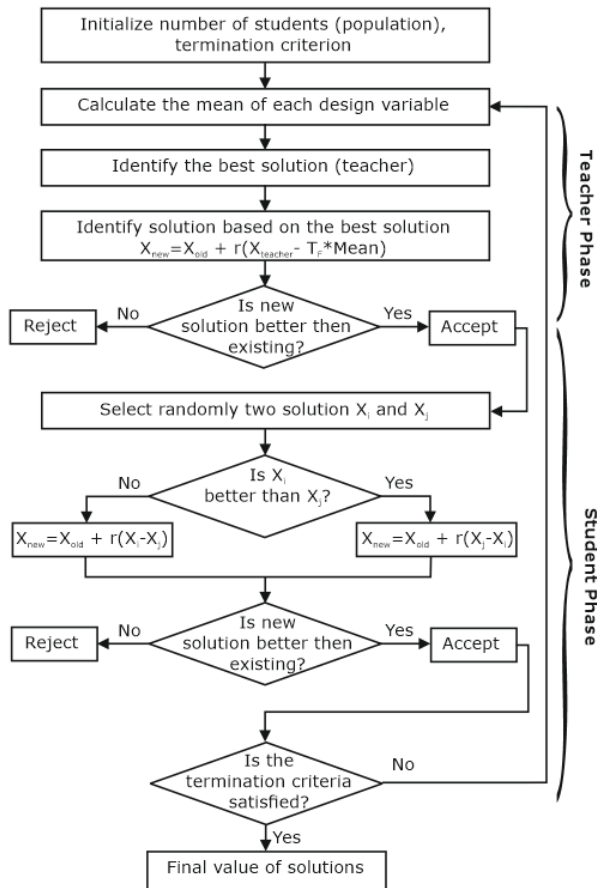


Figure 1. Flowchart of TLBO algorithm

3.1. Teacher phase

In this phase, students increase their knowledge during the teacher lecture. The professor tries to teach the students the material that is intended to be learned in that lecture. The professor is expected to be an expert in that field, and the students' grades will show how effective his lecture was. In this case for the i -th student is defined according to the following formula [4]:

$$X_{new_i} = X_{old_i} + rand * (Teacher - T_f * Mean) \quad (1)$$

$$Mean = \frac{1}{NP} \sum_{i=1}^{NP} X_i \quad (2)$$

$$TF = round [1 + rand(0,1)] \quad (3)$$

where X_{new_i} = new state of the student receive in the lecture phase,

X_{old_i} = old state of student,

$Teacher$ = best teacher,

T_f = teaching factor which will be 1 or 2,

$Mean$ = mean value of student group.

The student accepts the new state only if his/her grades have improved, if this is not the case then learning is dismiss and the student keep hold of the previous state of X_{old} .

3.2. Student phase

During this phase, students improve their knowledge by learning from each other, for example student X_i learns from randomly chosen student X_j , where $i \neq j$ holds. Depending on which student is better, the learning formulas apply [5]:

$$X_{new_i} = X_{old_i} + rand * (X_i - X_r) \quad (4)$$

$$X_{new_i} = X_{old_i} + rand * (X_r - X_i) \quad (5)$$

where X_{new_i} = new position of i -th student,

X_r = randomly selected student from the selected group,

$rand$ = randomly generated number in the interval $[0,1]$.

As with the lecture phase, the better student between the selected and randomly generated student will be selected and a new teacher phase will continue when the learning phase is over.

4. GTO ALGORITHM

The GTO algorithm (GTOA) aims to improve group of student knowledge using the group learning method and is based on rules [6]:

- Each student's ability to accept knowledge is different. The greater the difference between the students in the group, the greater the challenge for teachers in producing a curriculum.
- A good teacher usually pays more attention to students with a weak ability to accept knowledge.
- The student can expand their knowledge alone during extracurricular time, or in interaction with other students.
- A good teacher allocation mechanism is very helpful in improving student knowledge.

Group teaching approach are employed by developers. It uses different formats as teaching methods, like grouping of abilities, grouping of various abilities or/and different ages, etc. Education aims to enable students (learners) not only to acquire get knowledge, but also to become able to learn throughout life. Learning is more likely to be effective when the student plays a proactive role within the learning process. Strategies are determined by the topic being taught, and based on the character of the student.

It is definitely complicated to implement group teaching in practice due to the different talents

among students. To regulate group teaching to be suitable for use as an optimization technique, we first assume that student population, fitness value, and decision variables, correspond to the worst, average, and best group of students, subjects offered to students, and student knowledge.

The GTOA tool includes a group of computer intelligence techniques that provides an interface that permits students to practice the learned theory, as well as to verify and compare the characteristics of optimization methods [7].

This algorithm consists of four phases presented in Fig. 2:

1. Ability grouping phase
2. Teacher phase
3. Student phase
4. Teacher allocation phase.

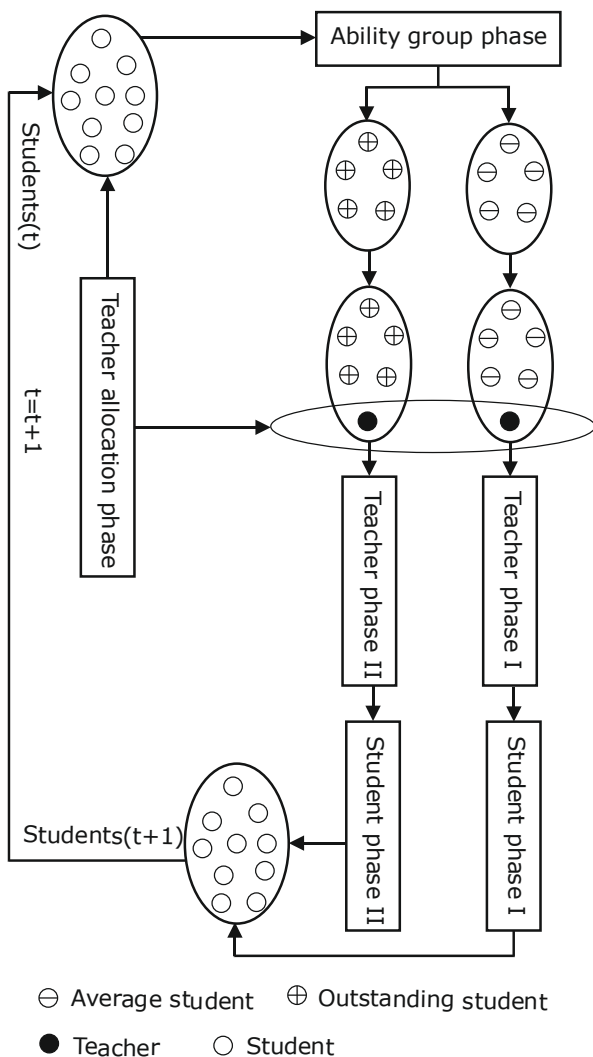


Figure 2. Phases for implementation of GTOA

4.1 Ability grouping phase

To better show the feature of group teaching, all students are divided into two small groups according to their ability of accepting knowledge in

GTOA. These two groups are equally important in GTOA. Thus, the two groups have the same number of students. One group with strong ability of accepting knowledge can be called outstanding group. Another group with poor ability of accepting knowledge can be called average group. The proposed GTOA determine that outstanding group has more knowledge than average group. It is easier for the teacher to adopt ability grouping method rather than traditional teaching method in terms of making the teaching plan. The teaching activities are larger in average group than in outsourcing group to achieve the same results. The ability of grouping is a dynamic process in GTOA, which is performed again after a learning cycle [8].

4.2. Teacher phase

Teacher phase means one student learns knowledge from his or her teacher, which corresponds to the defined second rule. The teacher makes different teaching plans for average group and outstanding group in the proposed GTOA.

Teacher phase I: In view of the strong ability of accepting knowledge, a teacher focuses on improving the knowledge of the outstanding group as a whole in the proposed GTOA as done in TLBO [6]. More specifically, the teacher can try his or her best to improve the mean knowledge of the whole class. In additional, the differences of accepting knowledge among students also need to be considered. Thus, the student of the outstanding group can gain his/her knowledge by

$$x_{teacher,i}^{t+1} = x_i^t + a \times (T^t - F \times (b \times M^t + c \times x_i^t)) \quad (4)$$

$$M^t = \frac{1}{N} \sum_{i=1}^N x_i^t \quad (5)$$

$$b + c = 1 \quad (6)$$

Where is:

- t - the current number of iterations,
- N - the number of students,
- x_i^t - the knowledge of student i at time t ,
- T^t - the knowledge of teacher at time t ,
- M^t - the mean knowledge of this group at time t ,
- F - the teaching factor that decides the teaching results of the teacher (can be either 1 or 2),
- $x_{teacher,i}^{t+1}$ - the knowledge of student i at time t by learning from teacher,
- a, b and c - the random numbers in the range $[0,1]$.

Teacher phase II: Considering the poor ability of accepting knowledge, a teacher pays more attention to the average group than outstanding group based on the second rule, who tends to improve the knowledge of the students from the perspective of individuals [6]. Thus, the student of the average group can gain his or her knowledge by

$$x_{teacher,i}^{t+1} = x_i^t + 2 \times d \times (T^t - x_i^t) \quad (7)$$

Where d is a random number in the range $[0, 1]$. In addition, one student may not gain knowledge by the teacher phase, which can be addressed by (take the minimum problem as an example)

$$x_{teacher,i}^{t+1} = \begin{cases} x_{teacher,i}^{t+1}, & f(x_{teacher,i}^{t+1}) < f(x_i^t) \\ x_i^t, & f(x_{teacher,i}^{t+1}) \geq f(x_i^t) \end{cases} \quad (8)$$

4.3. Student phase

The student phase including the Student phase I and the Student phase II corresponds to the mentioned third rule. During spare time, one student can gain his or her knowledge by two different ways: one through self-learning and the other through interaction with other students, which can be expressed as

$$x_{student,i}^{t+1} = x_{teacher,i}^{t+1} + e \times (x_{teacher,i}^{t+1} - x_{teacher,j}^{t+1}) + g \times (x_{teacher,i}^{t+1} - x_i^t) \quad \text{if } f(x_{teacher,i}^{t+1}) < f(x_{teacher,j}^{t+1})$$

$$x_{student,i}^{t+1} = x_{teacher,i}^{t+1} - e \times (x_{teacher,i}^{t+1} - x_{teacher,j}^{t+1}) + g \times (x_{teacher,i}^{t+1} - x_i^t) \quad \text{if } f(x_{teacher,i}^{t+1}) \geq f(x_{teacher,j}^{t+1}) \quad (9)$$

Where are:

e and g - random numbers in the range $[0,1]$,
 $x_{student,i}^{t+1}$ - the knowledge of student i at time t by learning from the student phase,
 $x_{teacher,j}^{t+1}$ - the knowledge of student j at time t by learning from the teacher.

As for the student j ($j \in \{1, 2, \dots, i-1, i+1, \dots, N\}$), student is randomly selected. In Eq. (9), the second item and the third item on the right mean learning from the other student and self-learning, respectively. In addition, one student may not gain knowledge by the student phase, which can be addressed by (take the minimum problem as an example)

$$x_i^{t+1} = \begin{cases} x_{teacher,i}^{t+1}, & f(x_{teacher,i}^{t+1}) < f(x_{student,i}^{t+1}) \\ x_{student,i}^{t+1}, & f(x_{teacher,i}^{t+1}) \geq f(x_{student,i}^{t+1}) \end{cases} \quad (10)$$

Where are:

x_i^{t+1} - the knowledge of student i at time $t+1$ after a learning cycle.

4.4. Teacher allocation phase

It is difficult task to improve the knowledge of students. Also, it is important to make a good teacher allocation. The teacher allocation in proposed method can be expressed as

$$T^t = \begin{cases} x_{teacher,i}^{t+1}, & f(x_{first}^t) \leq f\left(\frac{x_{first}^t + x_{second}^t + x_{third}^t}{3}\right) \\ \frac{x_{first}^t + x_{second}^t + x_{third}^t}{3}, & f(x_{first}^t) > f\left(\frac{x_{first}^t + x_{second}^t + x_{third}^t}{3}\right) \end{cases} \quad (11)$$

Where are:

$x_{first}^t, x_{second}^t, x_{third}^t$ - the first, second and third best students, respectively.

In order to accelerate the convergence of the proposed GTOA, outstanding group and average group share the same teacher.

4.5. Implementation of GTOA for optimization

In the following, the step-wise procedure for the implementation of GTOA is given and GTOA is explained with the aid of the flowchart in Fig. 3. [6].

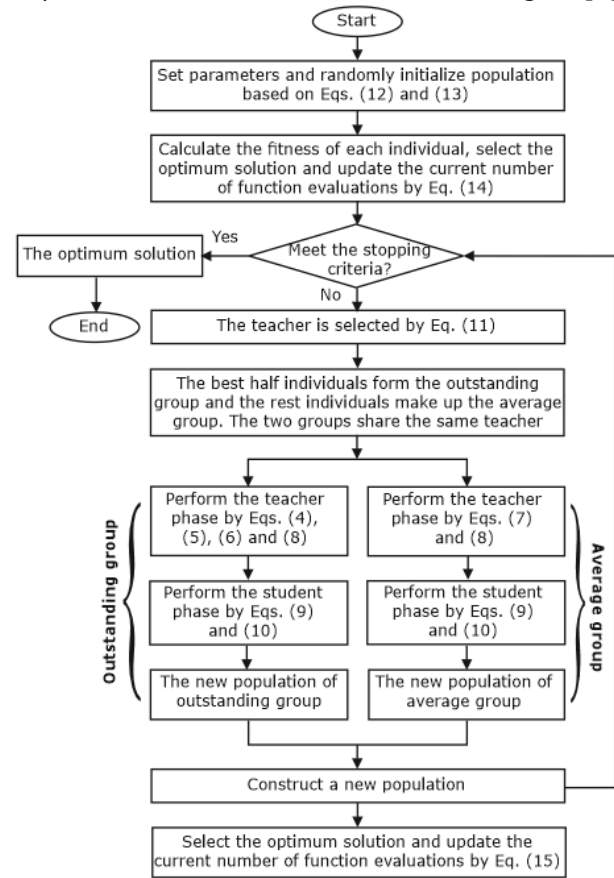


Figure 3. Flowchart of GTO algorithm

Step 1: Initialization parameters and population. These parameters include:

- T_{max} - the maximum number of function evaluations,
- $T_{current}$ ($T_{current}=0$) - the current number of function evaluations,
- N - population size,
- l - the lower bounds of design variables,
- u - the upper bounds of design variables,
- D - dimension of problem and
- $f(\bullet)$ - fitness function.

A random population \mathbf{X}^t is generated on the basis of the initialization parameters, which can be described as

$$\mathbf{X}^t = [x_1^t, x_2^t, \dots, x_N^t]^T = \begin{bmatrix} x_{1,1}^t & x_{1,2}^t & \dots & x_{1,D}^t \\ x_{2,1}^t & x_{2,2}^t & \dots & x_{2,D}^t \\ \dots & \dots & \dots & \dots \\ x_{N,1}^t & x_{N,2}^t & \dots & x_{N,D}^t \end{bmatrix} \quad (12)$$

$$x_{i,j}^t = l_i + (u_i - l_i) \times \kappa \quad (13)$$

where κ is a random number in the range $[0, 1]$.

Step 2: Population evaluation.

The optimal solution \mathbf{G}^t is selected and the fitness values of individuals are calculated. The current number of function evaluations $T_{current}$ is updated by

$$T_{current} = T_{current} + N \quad (14)$$

Step 3: Termination criteria.

If the current number of function evaluations $T_{current}$ is greater than the maximum number of function evaluations T_{max} , the algorithm stops and the optimal solution G^f is outputted. Otherwise, go to Step 4.

Step 4: Teacher allocation phase.

The first three best individuals are selected. Then the teacher T^t is calculated by Eq. (11).

Step 5: Ability grouping phase.

The student population is distributed into two groups based on the fitness values. The best half of individuals form the outstanding group and the rest individuals become the average group. These two groups share the same teacher. The outstanding group and the average group are marked as x_{good}^t and x_{bad}^t , respectively.

Step 6: Teacher phase and student phase.

For the group x_{good}^t , the teacher phase is implemented based on Eqs. (4), (5), (6) and (7). Then the student phase is conducted according to Eqs. (9) and (10). Finally, the new population x_{good}^{t+1} is obtained. For the group x_{bad}^t , the teacher phase is implemented based on Eqs. (7) and (8). Then the student phase is conducted according to Eqs. (9) and (10). Finally, the new population x_{bad}^{t+1} is obtained.

Step 7: Construct population. The population x_{good}^{t+1} and the population x_{bad}^{t+1} compose a new population x^{t+1} .

Step 8: Population evaluation. The fitness values of individuals are calculated and the optimal individual G_t is selected. The current number of function evaluations $T_{current}$ is updated by

$$T_{current} = T_{current} + 2N + 1 \quad (15)$$

Then Step 3 is executed.

5. COMPARISON OF TLBO AND GTO ALGORITHMS

Like GTOA, TLBO is also inspired from the teaching phenomenon in the classroom. A fundamental difference between TLBO and GTOA is that TLBO and GTOA imitate traditional teaching and group teaching, respectively. More specifically, their differences can be summarized as follows [6]:

1. In the teacher phase, GTOA considers the differences of accepting knowledge among students to make two different teaching methods as shown in Eqs. (2) and (5). However, TLBO uses the same teaching method for all students, which neglects the differences of accepting knowledge among students.
2. In the student phase, GTOA uses self-learning and interaction with other students to gain knowledge while TLBO only concerns the interaction with other students.
3. The ability grouping phase is introduced to GTOA, which is the distinct feature of the proposed GTOA. However, TLBO has not this phase.

4. The best student is regarded as teacher in TLBO while GTOA defines a teacher allocation mechanism related to the first three best students.

6. REVIEW OF GTO AND TLBO ALGORITHMS IMPLEMENTATION

The application of algorithms inspired by learning and teaching is diverse from the application in solving complex robot movements, scheduling processes in various types of systems, production systems, etc. The main goal of the implementation of these algorithms is to optimize a complex problem in order to reduce cost, time of production, procurement of spare parts, etc.

The implementation of TLBO and GTO algorithm is presented in Table 2 [10-15].

Although the GTO algorithm was developed in 2020, it has found applications in various fields of optimization in industry and technology.

Table 2. The implementation of TLBO and GTO algorithm

Application & Reference	Discussion
Mechanical design problems [1]	The method is tested on five different benchmark test functions with different characteristics, four different benchmark mechanical design problems and six mechanical design optimization problems which have real world applications. The effectiveness of the TLBO method is compared with the other population based optimization algorithms based on the best solution, average solution, convergence rate and computational effort. Results show that TLBO is more effective and efficient than the other optimization methods for the mechanical design optimization problems considered.
Engineering application [10]	The book offers a valuable resource for the development and usage of advanced optimization algorithms. TLBO algorithm can be used to solve continuous and discrete optimization problems in the fields of computer engineering, electrical engineering, manufacturing engineering, civil engineering, structural engineering, electronics engineering, mechanical design, thermal engineering, physics and biotechnology.
Balancing multi-objective two-sided assembly line [11]	Two-sided assembly line is designed to produce high-volume products such as trucks, cars, and engineering machinery. In this paper is considered minimization of the total relevant costs per product unit, maximization of the line efficiency, and minimization of the smoothness index. The proposed algorithm is tested on the benchmark instances and a practical case. Experimental results, compared with the ones computed by other algorithm and in current literature, validate the effectiveness of the proposed algorithm.

Power generated in ships using renewable sources [12]	In this paper is described minimization of total harmonic distortion in multilevel inverter (MLI) has been taken as an optimization problem and is solved using TLBO. MLI is a popular power electronic converter producing the desired output voltage from several DC input voltage sources like solar panels, batteries, and supercapacitors. The TLBO algorithm is applied to compute the optimum switching angles for MLI to produce the required fundamental output voltage with less harmonic distortion. This research outcome bears testimony to TLBO optimization's efficiency in improving the quality of the power generated in ships using renewable sources.
Resource-constrained project scheduling problem [13]	The main objective is the minimization of the makespan or total project duration. The TLBO algorithm has been used as additional features to enhance its exploration and exploitation capabilities. An activity list-based encoding scheme has been modified to include the resource assignment information because of the multi-skill nature of the algorithm. In addition, a genetic algorithm (GA) is also developed in this work for the purpose of comparisons. The computational experiments are performed on 216 test instances with varying complexity and characteristics generated for the purpose.
Unmanned aerial vehicle route planning [14]	This paper is considered constructs a 3-D flight environment model with multiple obstacles, and designs a novel diversified GTO algorithm for the generation of flight routes of unmanned aerial vehicles. In the environment model, a variety of obstacles are taken into consideration to make the flying scenarios more realistic. In the proposed algorithm, three novel teaching methods are introduced to balance the exploitation and exploration phases. The constraints are incrementally added to the fitness function to avoid the premature phenomenon in the initial iteration stage of algorithm. The experimental results show that the proposed algorithm is significantly superior and can always generate the optimal flight route in complicated environments.
Multi-product disassembly line balancing problems [15]	Remanufacturing systems play significant roles in end-of-life product recovery, environment protection and resource conservation. Disassembly is treated as a critical step in remanufacturing systems. Designing and applying highly efficient intelligent optimization algorithms to handle a many complex problems in the disassembly process. Here is presented a stochastic multi-product disassembly line balancing problem with maximal disassembly profit with disassembly time requirements. An enhanced GTO algorithm incorporating a stochastic simulation method is developed by considering developed model's features. Via performing simulation experiments on real-life cases is verify the excellent performance of the designed method in solving the real problem.

7. CONCLUSION

The implementation of optimization algorithms has a widespread application in various fields of science. Algorithms inspired by learning and teaching have emerged relatively recently, but their application is reflected in various aspects [16], from application in robot motion control, selection of optimal vehicle routing problems, to application in manufacturing systems, civil engineering [17], software development system, scheduling problem [18], logistics [19] and other important systems for the science development. These algorithms can be further improved to help solve various problems that require reduced production time, cost or human resources in performing various tasks.

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